



Spatial green growth in China: exploring the positive role of investment in the treatment of industrial pollution

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Abstract

The industrial sector of China is critical to the country's economic growth. On the other side, industrialisation has resulted in a high rate of emissions, pushing China to spend extensively on industrial pollution remediation. As a result, this study looks at the relationship between investment completed in the treatment of industrial pollution and economic development. Initially, the study used the global Moran's I test (Queen's contiguity matrix) to find spatial autocorrelation for the 'investment completed in the treatment of industrial pollution' factor, where the study found a positive association across Chinese provinces, and suggest the existence of spatial autocorrelation. Thereafter, a time-fixed effect spatial error model was used due to the lowest Akaike information criterion and Bayesian information criterion to analyse regional data of China from 1999 to 2018. The data reveal a positive association between investment completed in the treatment of industrial pollution and regional economic growth, both in the short and long term. Furthermore, the negative consequences of urban wages and foreign investment on investment completed in the treatment of industrial pollution are having the reverse effect on regional green development, necessitating ecologically friendly actions to mitigate the negative environmental effects of both. The results highlight the need for policymakers in other countries to review their plans for economic expansion and create environmentally friendly legislation. By implementing the Chinese green economic growth model, policymakers in industrially polluting nations can reduce industrial pollution and foster green growth in their nation.

Keywords Financial investment · Green growth · Industrial pollution · Urban wage · Spatial error model

JEL Classification E62 · Q56 · R23 · C21

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Introduction

One of the main purposes of industrial development is to improve people's living standards through creating employment, increasing wealth and enhancing their economic well-being. Industrial expansion, on the other hand, harms the natural environment as well as human and animal health (Fang 2011). The industrial sector consumes a large quantity of solid fuels, posing environmental risks such as air pollution, which have a detrimental impact on neighbouring residents. In addition, various enterprises that utilise wood as a fuel contribute to deforestation in the surrounding area, endangering the environment. According to Hayat et al. (2020), the industrial sector is the primary source of hazardous pollutants such as sulphur dioxide (SO₂), carbon dioxide (CO₂), biological oxygen demand (BOD), chemical oxygen demand (COD), total suspended solids (TSS) and solid waste (Xu et al. 2022; Qin et al. 2022; Tan et al. 2022).

These contaminants have a direct effect on human health and are responsible for a wide range of ailments in the population. As a result, as Fang (2011) pointed out, environmental organisations frequently propose alternative models and put pressure on businesses to reduce their share of pollutant discharge and move towards sustainable production.

To manage industrial pollution and reduce the detrimental consequences of industrialisation on the environment, environmental investments must be funded (Zhang et al. 2022; Wu et al. 2021; and Yin et al. 2021). In many developing countries, however, scarce public funds are usually directed to poverty-eradication projects rather than pollution-prevention efforts (Khan et al. 2022; Fang et al. 2022; Zhang et al. 2021). On the other side, industrial pollution control needs a well-coordinated policy framework as well as a sound investment strategy (Chen et al. 2021; Roudi et al. 2021; Chen et al. 2020).

The Chinese government has been working to help the industrial sector by improving policy settings that encourage the closure of less productive facilities, mergers and restructuring, and the implementation of binding environmental rules. Meanwhile, China's 13th Five-Year Plan included an emphasis on innovation as well as the notion of ecological civilisation (Quan et al. 2022; Yang et al. 2022; Tian et al. 2021b). This is a significant step forward in China's economic transition to a more balanced, high-quality and ecologically sustainable route. In addition, the federal government has added new criteria to its GDP-centred performance evaluation system to evaluate progress towards green development (Liu et al. 2022a; Ma and Zhu 2022; Quan et al. 2021). This will almost certainly motivate governments to prioritise environmental preservation and speed up the transition to a greener, more sustainable economic path (Kumar et al. 2022; Zhao et al. 2021). According to the Industrial upgrading for green growth in China: thematic focus on environment (2020), China's ongoing restructuring and relocating process aims to resolve structural imbalances and reallocates resources to more productive segments of the economy in order to achieve the dual goals of sustained economic growth and a progressive reduction of industrial pollution, which has been affecting the lives of those living near heavy industry clusters (Fang et al. 2021; Liu et al. 2022b; and Shang et al. 2021). If China wants to lessen the detrimental consequences of industrial pollution on human and animal health, it must control and reduce industrial pollution immediately (Fang et al. 2021; Guan et al. 2021; Pan and Chen 2021). The funding strategy for industrial pollution treatment has the potential to reduce industrial pollution and its negative consequences on human civilization (Yin et al. 2022; Tian et al. 2021a; Ge et al. 2019). This technique may be beneficial in determining how to reduce the gap between demand and supply for industrial pollution treatment investment, therefore aiding the achievement of environmental goals (Wang et al. 2022; Wu et al. 2021; Wu and Wu 2000). According to the experience of industrialised nations, investing in

the treatment of industrial pollution is a critical component of controlling industrial pollution and contributes to long-term economic growth (Wang et al. 2022; Gao et al. 2021; Lin et al. 2021). Market failure frequently manifests itself in environmental issues. Government investment in industrial pollution clean-up is a cost-effective strategy to improve environmental quality (Yan et al. 2019; Safi et al. 2021; Wahab et al. 2022).

The purpose of this research is to see how industrial pollution control investments affect economic growth. This study also looks at the influence of economic growth on investment in industrial pollution treatment. This study accomplishes these objectives by merging data from Chinese provinces with a more dynamic platform. This research will employ the spatial econometrics domain, and different popular spatial regression models will be simulated. The findings will also help policymakers evaluate existing industrial pollution treatment plans created by Chinese regions and implement major efforts to reduce industrial pollution and promote green growth in the country.

The following text is organised as a literature review regarding the subject study and is highlighted in the 'Literature review' section. The study's approach, which is based on spatial econometrics, is highlighted in the 'Methodology' section. The findings of the spatial regression for green growth and industrial pollution remediation are shown in the 'Results and discussion' section, and the conclusion and recommendations are presented in the 'Conclusions and recommendations' section.

Literature review

Through rapid economic development and industrialisation, the Chinese government has lifted approximately 400 million people out of poverty. Increased economic growth is being used by the Chinese government to help the remaining 200 million people living in poverty (World Development Indicators 2020). China's expanding industrialisation, on the other hand, has put additional pressure on the environment. According to the Asian Development Bank, China has eight of the top 10 cities with the worst air pollution. In 2007, China overtook the USA as the world's top emitter of carbon dioxide and greenhouse gases. According to LAN (2013), industrial pollution kills approximately 300,000 individuals in China each year. Rapid industrialisation increases energy use, material consumption and pollution. The Chinese government, according to Li et al. (2019), has made many attempts to encourage industrial transformation, drive structural changes and implement programmes aimed at increasing efficiency and performance. The industrial sector, in particular, has been essential in China's economic development. Between 1990 and 2015, the industrial sector created 48.88 percent of the Chinese GDP on average (Zhang

et al. 2019). Industrial pollution has become a big problem in China, according to Yan et al. (2019), garnering the attention of national and international environmental authorities.

Following the trend of developed nations, the Chinese government invests a large amount of money each year in the clean-up of industrial pollution. As a result, many Chinese scientists are more interested in investing in industrial pollution treatment. Fang (2011), for example, looked at the influence of pollution control investment at the provincial level on China's composite industrial cleaner index. The results of the study demonstrated a strong nonlinear relationship between the composite industrial cleaner index and the intensity of industrial pollution abatement investment. Yang (2016) assessed the efficiency of industrial pollution control investments at a macro level in China's Xinjiang region using a data envelopment analysis (DEA) approach. The study's findings indicated that Xinjiang's industrial pollution control investment had a low overall efficacy. This finding demonstrated that the industrial pollution management investment and production structure is irrational and inefficient. Su et al. (2018) investigated the relationship between air pollution and air pollution control investment in China from 2005 to 2014 using inverse distance weighted interpolation (IDW) and Pearson correlation approaches. The research found a relationship between China's air pollution index (API) and pollution mitigation investment. Furthermore, the research found an inverted U-shaped relationship between Chinese air pollution control spending and pollution levels.

Yan et al. (2019) focused on industrial waste gas emissions and looked at the influence of environmental protection spending on the reduction of industrial waste gas emissions in China from 2007 to 2016. The data demonstrate a discrepancy between industrial waste gas investment and overall industrial waste gas emissions. It also claims that managing industrial waste gas investment can assist China in reducing industrial waste gas emissions. Zhang et al. (2019) utilised the dynamic slacks-based measure (SBM) model to solve the question of how to increase desired industrial outputs and minimise unwanted industrial outputs with limited expenditure on industrial water pollution prevention for 30 Chinese provinces. The study used two output variables, two input variables and one carry-over variable. The outcome variables were industrial wastewater treatment and industrial output, whereas the input factors were industrial water consumption and facility operation costs, and the carry-over variable was an industrial waste. Based on the 'efficiency rank changes' of the 30 provinces from 2011 to 2015, the study discovered that places with more industrial production did not appear to have enhanced water efficiency. The efficiency rankings of the 30 provinces were extremely varied, with 13 provinces, including Beijing, Chongqing, Shandong, Guangdong and Sichuan,

scoring around zero. In addition, the majority of areas fail to create a balance between industrial production and industrial wastewater treatment, according to the research.

According to the findings of the previous study, investment in the treatment of industrial pollution significantly reduced industrial pollution in China. However, no one has evaluated the potential impact of industrial pollution treatment investments on China's economic development. Similarly, no one has addressed the influence of economic growth on investment in pollution clean-up in the industrial sector. The findings of this study will provide crucial insight into the influence of investment in the treatment of industrial pollution in stimulating green growth in the country in the area of spatial econometrics models.

Methodology

The research divided China's geographical region into seven areas, as illustrated in Fig. 1 and Table 1, according to the Natural Resource Defense Council (NRDC). While certain sections of the North, East, South, and Southwest have abundant water resources, the Central and Northwest have abundant agriculture commodities, according to Imran et al. (2017).

The study employs a spatial regression technique to discover regional heterogeneity in order to provide a realistic scenario of investment completed in the treatment of industrial pollution (ICTIP). According to Fang (2011) and Yang (2016), an increase or decrease in such investments will benefit or harm the local and surrounding areas. The findings of the global Moran's I, where Moran's I is supplied, were used to determine if there is a link and geographical autocorrelation between regional investment completed in the treatment of industrial pollution.

$$I = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\left[\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2 \right]^{1/2}} \quad \text{under } I = e' W e / e' e \quad (1)$$

Figure 2 shows that the estimate of Moran's I indicates a positive association, meaning that there is a cluster-based investment to minimise environmental concerns. In addition, spatial weights are determined using Queen's contiguity (Stetzer 1982).¹

$$w_{ij} = \begin{cases} 1 & \text{if } i, j \text{ are touching edge corner or boundary} \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

¹ Stetzer (1982) explained Queen's contiguity as a contiguity matrix where each region shares at least one single edge corner or boundary.

Fig. 1 Regional distribution of China**Table 1** Regional distribution of China

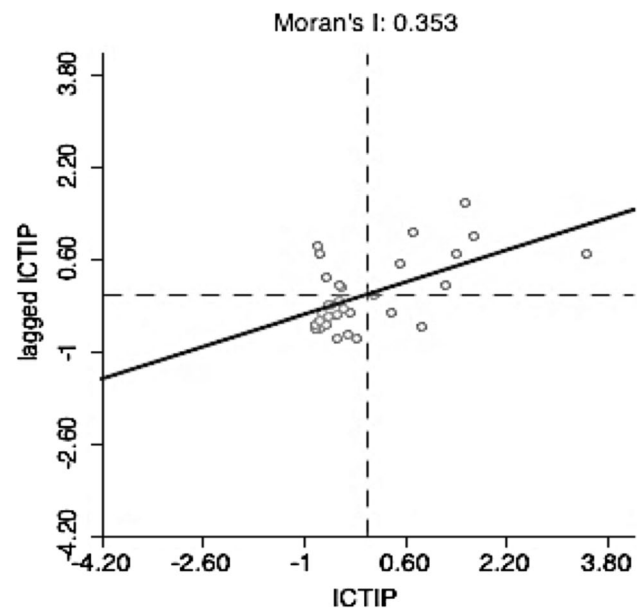
Region	Provinces
Centre	Hubei, Hunan, Henan, Jiangxi
East	Anhui, Fujian, Jiangsu, Shanghai, Shandong, Zhejiang
North	Beijing, Tianjin, Hebei, Shanxi, Inner-Mongolia
South	Guangdong, Guangxi, Hainan
Southwest	Sichuan, Yunnan, Guizhou, Chongqing
Northeast	Heilong Jiang, Liaoning, Jinan
Northwest	Ningxia, Xinjiang, Qinghai, Shan'xi, Gansu
Tibet	Xizang

Source: Natural Resource Defense Council (NRDC) (Imran et al. 2017)

After generating Queen's contiguity matrix, all weights and data were normalised in order to perform spatial regression. Geographically weighted regression (GWR) is a geographical regression based on spatial weights that includes spatial variability and eliminates the constraints of ordinary regression methodologies, according to Anselin (1988) and Elhorst (2003). To begin, a basic panel data model will be used (SPDM)² to determine ICTIP's multiplier effect on the independent variables used to measure green growth, which is supplied as

$$y_{it} = a + b \text{ICTIP}_{it,N} + c \psi_{it,N} + d \xi_{it,N} + e \varphi_{it,N} + \varepsilon_{it,N} \quad (3)$$

² For fixed effect model and random effect model, read Mutl and Pfaffermayr (2011).

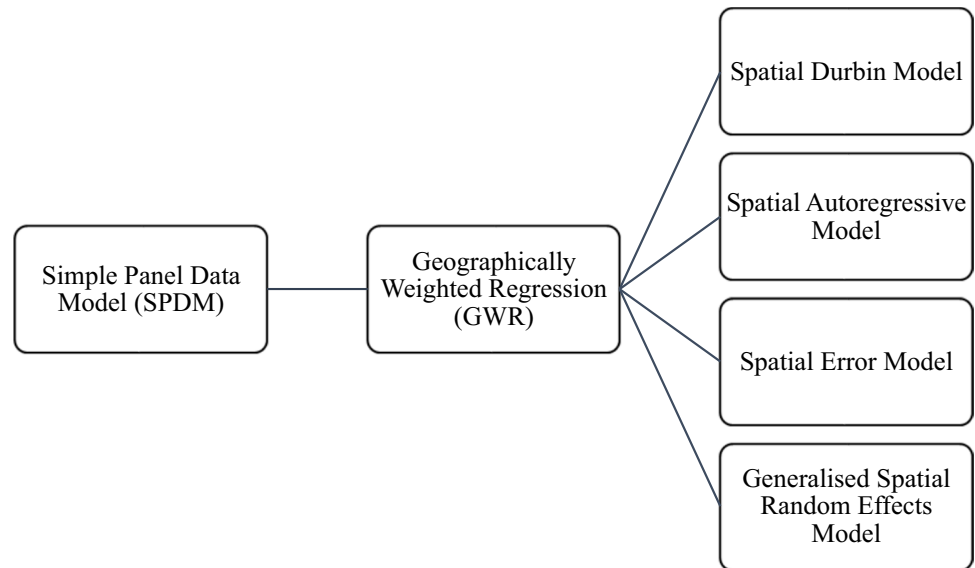
**Fig. 2** Moran's I for ICTIP

$$\text{ICTIP}_{it} = \alpha + \beta y_{it,N} + \gamma \psi_{it,N} + \vartheta \xi_{it,N} + \zeta \varphi_{it,N} + \delta_{it,N} \quad (4)$$

When dealing with economic entities that interact in space with one another, spatial econometrics takes into consideration the integration of space in econometric procedures. As a consequence, Eqs. (3) and (4) become Eqs. (3) and (4) after integrating spatial weights

$$y_{it} = a + \lambda \sum_{j=1}^N \omega_{ij,N} y_{jt,N} + b \text{ICTIP}_{it,N} + c \psi_{it,N} + d \xi_{it,N} + e \varphi_{it,N} + \mu_{it,N} \quad (5)$$

Fig. 3 Classification of SPDM to GWR regression



$$ICTIP_{it} = a + \lambda \sum_{j=1}^N \omega_{ij,N} ICTIP_{it,N} + b y_{it,N} + c \psi_{it,N} + d \xi_{it,N} + e \varphi_{it,N} + v_{it,N} \quad (6)$$

where y is the economic growth, $ICTIP$ is the completed industrial pollution treatment investment, ψ is the average wage of employees in urban units, ξ is the gross capital formation, and φ is the foreign direct investment inflow. While the second term on the right side of Eqs. (5) and (6) represents the spatial effect region ‘ i ’ receives from the region ‘ j ’s’ economic growth or $ICTIP$, the last term of each equation incorporates the error term, as ε and δ for simple panel data models (Eqs. (3) and (4)) and μ and ν for spatial panel regression (Eqs. (5) and (6)) addressing the error terms.

In addition, Anselin (2001) and Anselin et al. (2008) included different dynamic characteristics in GWR’s Eqs. (5) and (6). Such as for the incorporation of spatial-time-lag into GWR regressions, Anselin suggested ‘pure-space recursive’,³ for the incorporation of spatial-time-lag. For individual-time-lag, Anselin suggested ‘a time-space recursive’ model,⁴ whereas ‘time-space-simultaneous’ is suggested for incorporation of contemporaneous-spatial-lag and an individual-time-lag he suggested.⁵ Furthermore, to incorporate all types of spatial or time lags, Anselin suggested ‘time-space dynamics’.⁶

To determine the precise multiplier effect of selected parameters on green growth, we simulated multiple alternative spatial regressions (as shown in Fig. 3), including the spatial autoregressive model, the spatial Durbin model, the spatial error model and the extended spatial random-effects model. The spatial error model (SEM) was then

selected based on a number of easily available characteristics. We also employed a number of popular ways to replicate SEM, including SEM fixed effect, SEM random effect, SEM spatial fixed effect, SEM Lee-Yu, SEM time-fixed effect, SEM spatial time-fixed effect and SEM direct, indirect and total impact (as shown in Fig. 4) (Anselin 2001; Anselin et al. 2008).

This research concluded on SEM time-fixed effect under the $E = u_{it} * u_{it} = \sigma_{it}$ ⁷ it after evaluating the Akaike information criterion (AIC) and Bayesian information criterion (BIC).

This study’s SAR model is as follows:

$$y_{it} = a + \lambda \sum_{j=1}^N \omega_{ij,N} y_{it,N} + b ICTIP_{it,N} + c \psi_{it,N} + d \xi_{it,N} + e \varphi_{it,N} + \mu_{it,N} \quad (7)$$

$$u_{it,N} = \lambda \sum_{j=1}^N \omega_{ij,N} u_{it,N} + \epsilon_{it,N}$$

$$ICTIP_{it} = a + \lambda \sum_{j=1}^N \omega_{ij,N} ICTIP_{it,N} + b y_{it,N} + c \psi_{it,N} + d \xi_{it,N} + e \varphi_{it,N} + v_{it,N} \quad (8)$$

$$v_{it,N} = \lambda \sum_{j=1}^N \omega_{ij,N} v_{it,N} + \theta_{it,N}$$

While solving Eqs. (7) and (8) for SEM will give us Eqs. (9) and (10) (Baltagi et al. 2003, 2007; Kapoor et al. 2007), whereas, Eqs. (9) and (10) are true under $\varepsilon \sim N(0, \sigma^2 I_n) u_{it,N} = \lambda \sum_{j=1}^N \omega_{ij,N} u_{it,N} + \epsilon_{it,N}$ where $(1 - \lambda \omega_{ij,N}) \sum_{j=1}^N u_{it,N} = \epsilon_{it,N}$ then

$$(1 - \lambda \omega_{ij,N}) y_{it} = a(1 - \lambda \omega_{ij,N}) + b(1 - \lambda \omega_{ij,N}) ICTIP_{it,N} + c(1 - \lambda \omega_{ij,N}) \psi_{it,N} + d(1 - \lambda \omega_{ij,N}) \xi_{it,N} + e(1 - \lambda \omega_{ij,N}) \varphi_{it,N} + \epsilon_{it,N} \quad (9)$$

while solving Eq. (8) for SEM will give us Eq. (10), as given

$$v_{it,N} = \lambda \sum_{j=1}^N \omega_{ij,N} v_{it,N} + \theta_{it,N}$$

³ Su and Yang (2015)

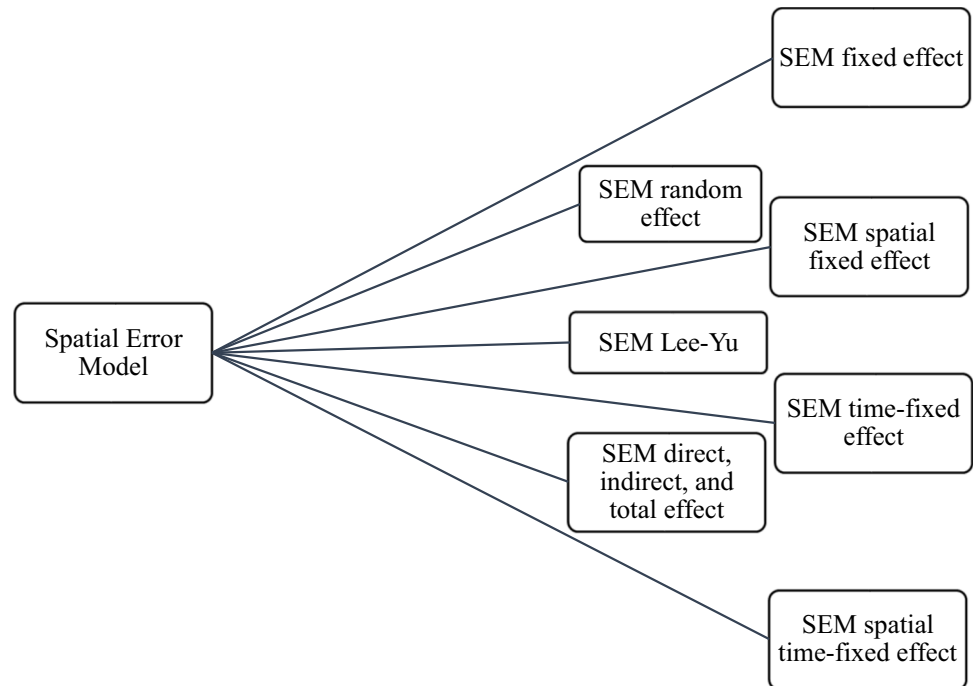
⁴ Korniotis (2010)

⁵ Yu et al. (2008) and Yu and Lee (2010)

⁶ See Hsiao (2014) and Alvarez and Arellano (2003)

⁷ σ_{it} represents the constant variance over time and space.

Fig. 4 Different regression simulated following spatial error model regression



$$\begin{aligned}
 &\text{where } (1 - \lambda\omega_{ij,N}) \sum_{j=1}^N v_{it,N} = \theta_{it,N} \\
 &(1 - \lambda\omega_{ij,N}) ICTIP_{it} = a(1 - \lambda\omega_{ij,N}) + b(1 - \lambda\omega_{ij,N}) y_{it,N} \\
 &+ c(1 - \lambda\omega_{ij,N}) \psi_{it,N} + d(1 - \lambda\omega_{ij,N}) \xi_{it,N} + e(1 - \lambda\omega_{ij,N}) \varphi_{it,N} + \theta_{it,N} \quad (10)
 \end{aligned}$$

Results and discussions

China's economy has grown at the quickest rate in the twentieth century, with unprecedented progress in practically every sector, yet this affluence has come with pollution. As a result, for the past three decades, China's economic progress, while expanding industrial production, has put the environment and livelihoods of local residents in peril. While ensuring long-term economic growth, the Chinese government continues to work hard to clean up their environment and reduce environmental concerns.

Table 2 provides descriptive statistics for the selected variables for the objectives of this study. Each area is anticipated to contribute 10.5 percent to the country's overall economic growth. Clean environmental risks and domestic capital development are also linked to regional economic growth. The fact that regional economic growth, ICTIP and domestic capital creation are all equal is a good sign because both economic growth and environmental investment will boost green growth, but the magnitude of the effect is uncertain. Furthermore, while the regional percentage of urban salaries is the greatest of all the factors investigated,

meaning that employees are more interested in transferring to urban units, the regional share of foreign direct investment is the lowest (Gao et al. 2020; Imran et al. 2020). The coefficients of variation for the variables range from 38.04 to 96.86 percent; however, foreign direct investment has the largest variance, which Fang (2011) attributes to significant differences in foreign direct investment intake into Chinese localities. The second-largest difference is in the percentage of ICTIP, implying significant regional inequalities in investment for industrial pollution treatment. Despite the fact that urban salaries vary the least and, as previously mentioned, the bigger proportion of urban earnings alludes to the assumption that almost every location implements the same share of urban migration (Imran et al. 2017; Yan et al. 2019).

The two key components that explain the degree of regional economic growth and the proportion of environmental upgrading are depicted in Fig. 5. The two graphs show how each region contributes to regional economic growth, concluding that higher levels of economic growth lead to a higher proportion of ICTIP in China, with the East contributing the most to regional economic growth, followed by the South in ICTIP and the North in regional economic growth.

This study compiled the results of each geographical regression for each dependent variable in order to better understand the magnitude of each factor influencing ICTIP on regional economic growth and the impact of regional economic growth on ICTIP. In addition, different variations of the spatial error model are considered in this study. The

Table 2 Descriptive statistics

Variable	Mean	Std. dev.	Coeff. var.
y: economic growth	0.1050	0.0712	67.81
ICTIP: investment completed in the treatment of industrial pollution	0.1040	0.0758	72.88
ψ : average wage of staff and workers in urban units	0.1091	0.0415	38.04
ξ : gross capital formation	0.1055	0.0685	64.93
φ : foreign direct investment	0.0990	0.0959	96.86

spatial random effect model (SRE) has columns 1 and 2, the spatial fixed effect model (SFE) has columns 2 and 9, the Lee-Yu spatial error model has columns 3 and 10, the time-fixed effect model (TFE) has columns 4 and 11, the spatial-time-fixed effect model (STFE) has columns 5 and 12, and the direct-indirect and total effect model (DITE) has columns 6 and 13, respectively, in Tables 3 and 4. The results of the diagnostic tests are included in the last column of both tables, with no indication of endogeneity in both spatial regression and *R*-square values ranging from 0.709 to 0.986.

The regression findings for SPDM based on Eqs. (3) and 4 are provided in the first column of Table 3 and Table 4. Because SPDM overlooks the geographical term in favour of data, Table 3 can include any specified aspect that has a significant influence on the country's economic growth. ICTIP alone accounts for 13% of regional economic growth, while domestic capital formation, which accounts for 83 percent, has the biggest impact. Meanwhile, urban salaries are having a negative influence on regional economic growth. It was revealed that the time-fixed effect error model, which has the lowest AIC and BIC values, is better suited for subject data after modelling a large number of geographical regressions and comparing their AIC and BIC values.

China's success story for the selected time period is summarised in Table 3. According to the time-fixed effect model in Eq. (9), the ICTIP adds 13 percent to regional green economic growth. While the urban wage rate has a negative impact on regional green economic growth (currently 19%), it has a favourable impact on the other geographical regressions (20–22%). Because metropolitan salaries are a major draw for urban migration and China's regional economic growth is being hindered by an overcrowded urban population, the TFE results are more plausible (Imran et al. 2020, 2017, 2019). This suggests that raising employee pay affects regional green economic development, meaning that workers may be spending a significant percentage of their pay on environmentally detrimental activities (Khalil et al. 2022). Local capital has a nearly 70% larger impact on regional green economic growth than FDI, implying that increased domestic investment promotes faster regional green economic growth.

Because this study discovered that an increase in ICTIP led to regional green economic growth, Table 4 also includes the results for selected parameters as well as the long-run economic growth impact on ICTIP as calculated by Eq. 10, because this study found that an increase in ICTIP led to regional green economic growth, as shown in Table 3. But,

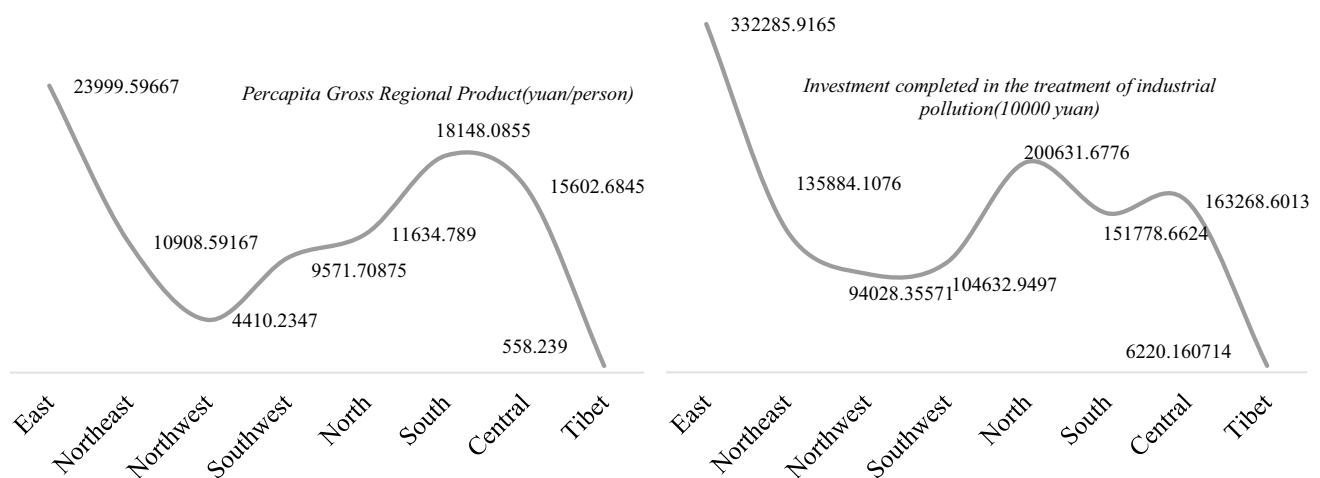
**Fig. 5** Regional distribution of gross regional product and ICTIP in China

Table 3 Results of the spatial error regressions with economic growth and investment completed in the treatment of industrial pollution

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
y	SPDM	SRE	SFE	TFE	STFE	Lee-Yu	DITE	Hausman
ICTIP	0.134*** (0.0286)	0.0695* (0.0366)	0.0673* (0.0357)	0.133*** (0.0373)	0.0679** (0.0344)	0.0673* (0.0357)	0.0695* (0.0366)	0.0695*** (0.0133)
ψ	−0.180*** (0.0338)	0.224* (0.121)	0.208* (0.120)	−0.197*** (0.0712)	0.210* (0.117)	0.208* (0.120)	0.224* (0.121)	0.224*** (0.0698)
ξ	0.828*** (0.0318)	0.247*** (0.0574)	0.240*** (0.0560)	0.831*** (0.0802)	0.239*** (0.0565)	0.240*** (0.0560)	0.247*** (0.0574)	0.247*** (0.0317)
φ	0.128*** (0.0128)	0.0348** (0.0164)	0.0334** (0.0150)	0.132*** (0.0258)	0.0335** (0.0161)	0.0334** (0.0150)	0.0348** (0.0164)	0.0348*** (0.00737)
Lambda		−0.0848 (0.114)	−0.0982 (0.118)	0.178 (0.322)	−0.111 (0.151)	−0.0982 (0.118)	−0.0848 (0.114)	−0.0848 (0.131)
ln_phi		4.974*** (1.009)					4.974*** (1.009)	4.974*** (0.528)
sigma2_e		1.12e−05** (5.46e−06)	1.06e−05** (5.16e−06)	6.75e−05*** (1.70e−05)	1.06e−05** (4.81e−06)	1.12e−05** (5.43e−06)	1.12e−05** (5.46e−06)	1.12e−05*** (1.29e−06)
Constant	0.011*** (0.0023)	0.0439* (0.0235)					0.0439* (0.0235)	0.0439*** (0.0160)
Observations	160	160	160	160	160	152	160	160
R-squared	0.986	0.930	0.932	0.986	0.932	0.932	0.930	0.930
Number of regions		8	8	8	8	8	8	8
AIC (BIC)	−771.384 (−752.93)	−1291.62 (−1270.1)	−1365.81 (−1347.3)	−1366.78 (−1348.3)	−1068.94 (−1050.49)	−1289.11 (−1270.97)	−1291.62 (−1270.9)	−1289.622 (−1289.62)
Hausman endogeneity test								2.62

Standard errors in parentheses

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

in the short and long terms, how will ICTIP affect economic development, as well as other factors? As a result, the SPDM and other spatial regression outcomes were tallied in Table 4, with the time-fixed model's results being more appropriate based on the lowest AIC and BIC values.

TFE's findings for ICTIP reveal that regional economic growth is positively significant in both the long and short runs, meaning that a 1% rise in regional economic development in the short run improves the ICTIP by 71.6 percent on average, whereas a 1% increase in long-run regional economic growth increases the ICTIP by 100%; this means that every region is attempting to contribute a significant amount of investment to cure its industrial pollution, and that these regions will increase their investment to treat industrial pollution as economic growth accelerates. Furthermore, the average urban wage is positively significant, showing that a unit increase in the urban wage rate has a 56 percent positive multiplier effect on ICTIP, implying that an increase in employee income enhances ICTIP. This conclusion

is logical since employees may spend a significant amount of their wages on environmentally friendly things, resulting in an increase in regional environmental investment. Furthermore, both gross capital creation and foreign direct investment (FDI) have a negative impact, which is startlingly similar. This means that China's economy has reached its investment peak, and that any further increases in investment, whether domestic or foreign, will hurt the ICTIP. According to Li et al. (2019), the relevance of this discovery may be seen in the Chinese government's recent harsh environmental actions.

In summary, we found that ICTIP greatly contributed to the economic growth of Chinese regions, resulting in green economic growth, as shown in Tables 3 and 4. In contrast, an increase in China's regional economic growth, both short and long term, boosts ICTIP investment by multiples.

This study displayed three alternative maps using the NRDC regional division to present the data and

Table 4 Results of the spatial error regressions with investment completed in the treatment of industrial pollution and economic growth

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ICTIP	SPDM	SRE	SFE	Lee-Yu	TFE	STFE	DITE	Hausman
y	1.023*** (0.269)	0.707** (0.304)	2.336* (1.397)	2.336* (1.397)	0.716** (0.302)	2.505 (1.614)	0.707** (0.304)	0.707*** (0.170)
y ²	0.746*** (0.195)	1.018*** (0.157)	−1.232 (5.283)	−1.232 (5.283)	1.009*** (0.160)	−2.104 (6.795)	1.018*** (0.157)	1.018*** (0.222)
ψ	0.662*** (0.0760)	0.554*** (0.0673)	−0.683 (1.148)	−0.683 (1.148)	0.558*** (0.0886)	−0.650 (1.153)	0.554*** (0.0673)	0.554*** (0.0706)
ξ	−0.187 (0.185)	−0.107 (0.260)	−0.205 (0.302)	−0.205 (0.302)	−0.123** (0.241)	−0.194 (0.354)	−0.107 (0.260)	−0.107 (0.168)
φ	−0.133*** (0.0432)	−0.134** (0.0598)	−0.171* (0.101)	−0.171* (0.101)	−0.129* (0.0715)	−0.168* (0.0980)	−0.134** (0.0598)	−0.134*** (0.0374)
Lambda		−0.437*** (0.117)	−0.340** (0.143)	−0.340** (0.143)	−0.467*** (0.124)	−0.372*** (0.115)	−0.437*** (0.117)	−0.437*** (0.105)
ln_phi		−15.53*** (4.015)					−15.53*** (4.015)	−15.53 (575.0)
sigma2_e		0.000378*** (7.02e−05)	0.00032*** (5.18e−05)	0.00034*** (5.45e−05)	0.00037*** (7.93e−05)	0.00031*** (5.75e−05)	0.00038*** (7.02e−05)	0.00038*** (4.34e−05)
Constant	−0.031*** (0.0063)	−0.0222*** (0.00721)					−0.0222*** (0.00721)	−0.0222*** (0.00534)
Observations	160	160	160	152	160	160	160	160
R-squared	0.923	0.923	0.729	0.729	0.923	0.709	0.923	0.923
Number of regions		8	8	8	8	8	8	8
AIC (BIC)	−1068.15 (−1052.8)	−782.2282 (−757.6268)	−814.2478 (−792.7215)	−765.0388 (−743.871)	−817.5778 (−796.0516)	−787.592 (−766.066)	−782.2282 (−757.627)	−780.2282 (−752.5517)
Hausman endogeneity test								12.84*

Standard errors in parentheses

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

demonstrate how much each component contributed to the ICTIP. Figure 6 displayed ICTIP's impacts on regional industrial production. Figure 7 depicted ICTIP's effects on urban wages. Figure 8 depicted ICTIP's effects on domestic capital.

Starting with Fig. 6, it can be seen that the ratio of ICTIP to regional industrial production is better for the rest of China, except for the South, which has the worst results and is environmentally degraded, and some parts of Central China and Qinghai in the Northwest, which also have an unbalanced ratio of ICTIP to industrial production.

Figures 7 and 8 show that the emphasis of labour and capital migration is to the north, east and central China, respectively, as shown in Fig. 6; each figure represents a proportion of ICTIP and the subject factor. Figure 7's distribution is clustered and looks to be more in level shape, where the dark-shaded level is made up of the

'delta region',⁸ which is known for its economic growth and success, attracting skilled individuals from all across the country every year to optimise their utility level. The second level, which is dark grey in hue, brings together territories from the Central, North and Northeast. These locations are benefiting from the 'delta-region' spillover effect, offering the cheapest and nearest place for labour to live and work and the second-best alternative for labour. The third and fourth places are less desirable for workers to relocate there and begin working.

When these maps are compared to Table 4, a few key conclusions emerge. First, regional economic development accounts for 71 % of the ICTIP, as shown in Fig. 4 by the dark, medium and light-grey hues that span more than half of China. As a result, China must concentrate

⁸ Li et al. (2019)

Fig. 6 The ratio of ICTIP to industrial production (the year 2018)



Fig. 7 The ratio of ICTIP and urban wage (the year 2018)



on regional green economic growth to enhance its environment or enact environmentally friendly laws. Second, wages paid to workers in urban areas have a significant influence on the ICTIP; however, when compared to Fig. 7, this significant impact is limited to the North and certain parts of East and Central China. As a result, it emphasises the fact that China's wage rate is unequal across the country, and its contribution to ICTIP is influenced by distance from coastal lines. As a result, the government must equalise pay rates throughout China so that customers may purchase environmentally friendly goods and services. Finally, when comparing Fig. 8 to Table 4's results for domestic capital, it can be seen that domestic investment is adversely related to ICTIP, but when looking at Fig. 8, it seems more like Fig. 6. Because the

map is produced on a regional basis while regression is simulated on a macro level, the results in Table 4 contradict each other. Domestic capital makes a considerable contribution to ICTIP, albeit the quantity varies by area, and the impact of domestic capital on ICTIP is negative at the macro level.

Conclusion and recommendations

We examine the impact of investment completed in the treatment of industrial pollution on regional economic growth in this study. The impact of regional economic growth on the investment completed in the treatment of industrial pollution is also examined in this study, for the purpose this study

Fig. 8 The ratio of ICTIP and domestic capital (the year 2018)



utilises the provincial panel data of 30 Chinese provinces from 1999 to 2018. The study simulated global Moran's I (following Queen's contiguity matrix) shows the existence of spatial autocorrelation between investment completed in the treatment of industrial pollution. Further spatial error model, many geographic regression models are simulated, with the findings of the time-fixed effect spatial error regression model being determined to be more appropriate based on the lowest AIC and BIC values.

The findings demonstrate that investment completed in the treatment of industrial pollution has a beneficial impact on China's regional economic growth. On the other hand, regional economic growth has a favourable and considerable influence on the investment completed in the treatment of industrial pollution in the short and long run. This implies that the investment completed in the treatment of industrial pollution both encourages and boosts regional green economic growth in China's regions. Furthermore, whereas gross capital creation and foreign direct investment have a favourable influence on regional economic growth, they hurt investment completed in the treatment of industrial pollution. Because investment completed in the treatment of industrial pollution and regional economic growth have a beneficial relationship, the Chinese government must embrace environmentally friendly policies and pave the road for green economic growth. While the impact of urban wages on regional economic growth is generally negative, it is beneficial in the case of the investment completed in the treatment of industrial pollution. This conclusion is striking since, based on the first and second observations about urban wages, one may assume that people in developed regions live in an ecologically responsible manner despite the strong pressure of urban migration.

Recently, Chinese authorities have been battling to find and create various environmentally friendly solutions for reducing industrial pollution and boosting regional green economic growth in the country. Investment completed in the treatment of industrial pollution would be an excellent choice in this respect because it decreases industrial pollution while also promoting green economic growth in the country. However, we found the least investment completed in the treatment of industrial pollution in several parts of China, such as Tibet, the Northwest and the Southwest. As a result, China's environmental authorities are now responsible for increasing investment completed in the treatment of industrial pollution in these locations since it offers green economic growth.

Policy implication and limitation of the study

Furthermore, authorities should consider enhancing regional economic growth in comparatively poorer regions and monitoring the ratio of investment completed in the treatment of industrial pollution to industrial production as a consequence of the finding that increased regional economic growth in China boosts investment completed in the treatment of industrial pollution. The authorities will be able to accomplish green economic growth and balance the pressure of urban migration after the rate of economic growth in poor regions has improved and the investment completed in the treatment of industrial pollution to industrial production ratio has been balanced. Furthermore, the findings will aid policymakers in other nations in revising their economic growth strategies and developing ecologically friendly legislation. Policymakers in industrial polluting nations may minimise industrial pollution and create green economic

growth in their country by adopting the Chinese green economic growth model.

Data availability The article does not include any kind of unauthorised, restricted and illegal material and data.

Author contribution The idea of the current paper is first presented by Dr. Muhammad Imran; with the help of the remaining co-authors, he accomplished his task. Dr. Muhammad Imran designed the ‘Methodology’ section and simulated and listed the results for spatial econometric regression. Dr. Naveed Hayat and Mr. Salman Wahab appreciated the idea and helped in drafting and, particularly, revising the manuscript, where they put forward several modifications and amendments at different stages of the manuscript. Dr. Muhammad Ali Saeed and Dr. Abdul Sattar helped with data management, approving the results, and also helped in proofreading. All authors read and approved the final manuscript.

Declarations

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